DESIGN OPTIMIZATION OF ANN-BASED PATTERN RECOGNIZER FOR MULTIVARIATE QUALITY CONTROL

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ABSTRACT

In manufacturing industries, process variation is known to be major source of poor quality. As such, process monitoring and diagnosis is critical towards continuous quality improvement. This becomes more challenging when involving two or more correlated variables or known as multivariate. Process monitoring refers to the identification of process status either it is running within a statistically in-control or out-of-control condition, while process diagnosis refers to the identification of the source variables of out-of-control process. The traditional statistical process control (SPC) charting scheme are known to be effective in monitoring aspects, but they are lack of diagnosis. In recent years, the artificial neural network (ANN) based pattern recognition schemes has been developed for solving this issue. The existing ANN model recognizers are mainly utilize raw data as input representation, which resulted in limited performance. In order to improve the monitoring-diagnosis capability, in this research, the feature based input representation shall be investigated using empirical method in designing the ANN model recognizer.

ABSTRAK

Dalam industri pembuatan, variasi proses yang dikenalpasti sebagai sumber utama masalah kualiti. Oleh itu, pemantauan proses dan diagnosis adalah penting ke arah penambahbaikan kualiti yang berterusan. Ini menjadi lebih mencabar apabila melibatkan dua atau lebih pembolehubah kaitan atau dikenali sebagai multivariat. Pemantauan proses merujuk kepada pengenalan status proses sama ada ia sedang berjalan dalam statistik dalam kawalan atau keadaan di luar kawalan, manakala diagnosis proses merujuk kepada pengenalan pembolehubah proses sumber luar kawalan. Proses Kawalan Statistik (SPC) menggunakan carta statistic tradisional diketahui berkesan dalam aspek pemantauan, tetapi kekurangan dari aspek diagnosis. Dalam tahun-tahun kebelakangan ini, skim rangkaian neural tiruan (ANN) berasaskan pengiktirafan corak telah dibangunkan untuk menyelesaikan isu ini. Model pengenal (recognizer) rangkaian neural tiruan (ANN) yang sedia ada kebanyakannya menggunakan data mentah sebagai perwakilan input, yang menghasilkan prestasi yang terhad. Dalam usaha untuk meningkatkan keupayaan pemantauan diagnosis, dalam kajian ini, ciri perwakilan input berasaskan akan disiasat menggunakan kaedah empirikal dalam bentuk model ANN Pengenal.

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LIST OF ABBREVIATIONS

ANN - Artificial neural network

BPN - Back propagation network

BPR - Bivariate pattern recognition

CCPs - Control chart patterns

CUSUM - Cumulative sum

EWMA - Exponentially weighted moving average

LCL - Lower control limit

LEWMA - Last value of exponentially weighted moving average

MCUSUM - Multivariate cumulative sum

MEWMA - Multivariate exponentially weighted moving average

MPR - Multivariate pattern recognition

MQC - Multivariate quality control

MSD - (Mean) x (standard deviation)

MSE - Mean square error

MSPC - Multivariate statistical process control

PR - Pattern recognition

RA - Recognition accuracy

SPC - Statistical process control

SPCPR - Statistical process control pattern recognition

LIST OF SYMBOLS

α - Type I error (α risk)

β - Type II error (β risk)

λ - Constant parameter for EWMA control chart

ρ - Correlation coefficient for bivariate samples

μ - Mean

σ - Standard deviation

μ_0 - Mean for in-control samples

σ_0 - Standard deviation for in-control samples

σ_{12} - Covariance for bivariate samples

X^2 - Chi-square statistics

Σ - Covariance matrix for bivariate samples or basic summation

t_0 - time/point the sampling begins or the shift begins

X_t - Original observation samples at time/point t

Z_t - Standardized observation samples at time/point t

σ' - Random noise level for stratification pattern

s - Mean shift for sudden shift patterns

g - Trend slope for trend patt

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CHAPTER 1

INTRODUCTION

1.1 Introduction

There are various definitions of quality; Dr. Armand Feugenbaum, states that "Quality is a customer determination which is based on the customer's experience with the product or service, measured against his or her requirements – stated or unstated, conscious or merely sensed, technically operational or entirely subjective – and always representing a moving target in a competitive market" (Summers, 2007) . High quality of product is the vital concern for most of the companies that will survive in this highly competitive global market. One of the most effective approaches to achieve high product quality is through the applications of Statistical Process Control (SPC).

Statistical Process Control (SPC) has become an important approach or tool for process industries until these days. Statistical process control (SPC) is a powerful and commonly used tool to improve product quality by using statistical tools and techniques to monitor, control and improve processes. The aim of SPC is to achieve higher product quality and lower the production cost due to the minimization of the defect product. One of the most commonly used tools is the statistical process control chart developed by Dr. Walter A. Shewhart (Shewhart, 1931), which is known as "The Control Chart". Basically, a control chart is a plot of a process characteristic, usually over time with statistically determined limits. When used for monitoring process variation, it helps the user to determine the appropriate type of action to take on the process.

Process variation has been known to be a major source of poor quality in manufacturing industries. Monitoring process variation is important in the process of achieving best quality of product, which involves the identification of process status, either it is running within a statistically in-control or out-of-control condition. Process diagnosis refers to the identification of the source of variables of out-of-control process.

In reality, manufacturing processes involve two or more dependent variables, and therefore an appropriate scheme is required to monitor and diagnose those variables simultaneously. If this is the case, monitoring those variables separately using univariate SPC would inevitably expose to the high possibility of false alarms occurrence and this shall lead to wrong decision making which due to inaccurate data. The suitable technique which shall be used in this case, is known as Multivariate Quality Control (MQC). It is basically an extension of simple univariate (one variable at a time) quality control.

1.2 Statement of the Problem

Diagnosis of process variation is vital towards continuous quality improvement and when involving two or more dependent variables (multivariate). An appropriate scheme is needed to perform diagnosis. The existing ANN models recognizers mainly utilize raw data as input pattern representation, which resulted in limited performance. The Feature-Based ANN model is expected to perform better than the one which utilize raw data as input representation. The performance of Feature-Based ANN model depends a lot on the selection of the right and suitable combination of statistical features. In this research, the selection of suitable statistical features shall be achieved by using Forward Selection. The monitoring-diagnosis capability shall be improved using the application of Taguchi Design of Experiment.

1.3 Purpose of the Research

The purpose of this research is to design, develop and test runs a scheme for enabling accurate diagnosis of multivariate (bivariate) process mean shifts. The characteristics of the scheme are applicable for bivariate process (correlated data streams) and on-line situation (dynamic data streams). The diagnosis capability shall be improved by the application of design of experiment technique during the selection of feature input representation.

1.4 Objectives

The objectives of this research are:

(i) To develop a statistical feature-ANN scheme for enabling diagnosis of multivariate process variation.

(ii) To improve the diagnosis performance using feature-based ANN pattern recognition scheme applying empirical method technique in selection of feature input representation in ANN model recognizer.

1.5 Scope and Key Assumptions

The scopes of this research are:

(i) Multivariate quality control cases are limited to bivariate process, that is, only two dependent variables being monitored and diagnosed.

(ii) Bivariate process variables are dependent on each other based on linear cross correlation (ρ).

(iii) In a statistically out-of-control condition, predictable bivariate process patterns are limited to sudden shifts (upward shifts and downwards shift) in the source variables.

(iv) Bivariate process variation is limited to changes in mean shifts at specified data correlation, or changes in data correlation at specified mean shifts.

(v) Magnitudes of mean shifts in the source variables are limited within ± 3 standard deviations based on control limits of Shewhart control chart.

(vi) The foundation modelling and simulation for bivariate correlated samples are based on established model (Lehmann, 1977).

1.6 Definition of Terms

The following terms are important and frequently used in this research:

(a) On-line process

On-line process refers to in-process environment in manufacturing industries, that is, during manufacturing operation is running. Based on individual samples, continuous data streams patterns will be produced through automated measuring and inspection devices. An in-control process is represented by random/normal patterns, while an out-of-control process is represented by gradual trend or sudden shift pattern.

(b) Process monitoring and diagnosis

Process monitoring refers to the identification of process status either it is running within a statistically in-control or has become a statistically out-of-control. Process diagnosis refers to the identification of sources of variation in relation to a statistically out-of-control process.

(c) Sources of variation

Source of variation refers to a component variable or group of component variables that indicate a bivariate process has become out-of-control. In this research, it is focused on sudden shift in process mean (process mean shifts). This information is useful towards diagnosing the root cause error.

(d) Accurate diagnosis

Accurate diagnosis refers to a desirable diagnosis performance, that is, effective to correctly identify the sources of variation with high recognition accuracy (> 95%).

(e) Control chart patterns (CCPs)

Control chart patterns refer to the patterns of univariate process data streams that can be indicated graphically using Shewhart control chart.

(f) Bivariate patterns

Bivariate patterns refer to the unified patterns that are able to indicate the linear correlation between two dependent variables. In this research, these patterns are represented graphically using scatter diagrams.

(g) Pattern recognition

Pattern recognition is an operation of extracting information from an unknown process data streams or signals, and assigning it to one of the prescribed classes or categories (Haykin, 1999). In this research, it deals with bivariate patterns.

(h) Pattern recognition scheme

Pattern recognition scheme refers to a set of related procedures formulated and presented in a unified manner for addressing the problem of control chart pattern recognition (Hassan, 2002).

1.7 Expected Outcomes

The main outcome of this research would be a representative pattern recognition scheme namely features-based ANN as a proof of improvement. The intended scheme should be capable of identifying the sources of variables of multivariate process variation.

The design strategy in developing an intended scheme involves application of the existing methods and investigation on improved methods. The existing method includes modelling of multivariate process samples and patterns, which is less reported in this field. The improved methods include the design of statistical features input pattern representation and an ANN model recognizer using empirical method.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter provides a review on the existing researches related to the subject of this thesis which includes a general review on process variation which is known to be the source of poor quality and then followed by the use of SPC to monitor univariate process variation and multivariate process variation. Also, the limitation of multivariate quality control (MQC) and research works in multivariate statistical process control (MSPC), and statistical process control pattern recognition (SPCPR) schemes are also reviewed.

2.1 Process Variation

In manufacturing and service industries, the goal of most processes is to produce products or provide services that exhibit little or no variation. Variation, where no two items or services are exactly the same, exists in all processes (Summers, 2006). Process variation and process precision are closely related, whereby a process with little variation is said to be 'precise'. Most processes are designed with controls that can be used to adjust the process mean, and hence increase the accuracy. Reducing the amount of process variation is usually a difficult task.

As mentioned earlier, variation in manufacturing process environment causes the parts or products to be produced in different size and properties. Process variation as shown in Figure 1 can be influenced by chance causes (random error) and/or assignable causes (systematic errors). The figure shows that from initial time t_0 to period t_1, process mean (μ_0) and standard deviation (σ_0) are in-control. Disturbance due to assignable causes can be indicated in three situations. Firstly, at time t_1, an assignable cause may shift the process mean ($\mu_1 > \mu_0$) but maintain the dispersion (σ_0). Secondly, at time t_2, it may change the dispersion ($\sigma_2 > \sigma_0$) but maintain the mean (μ_0). Thirdly, at time t_3, other assignable cause may effects both process mean and dispersion to be out-of-control, $\mu_3 < \mu_0$ and $\sigma_3 > \sigma_0$.

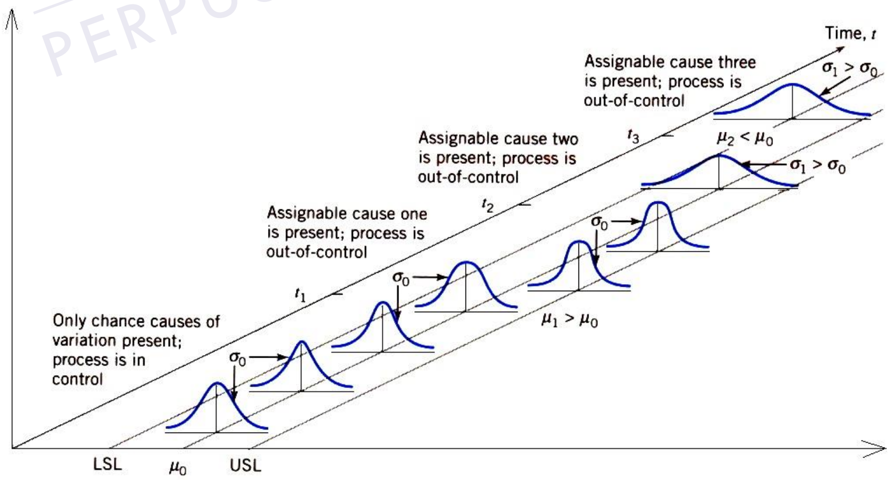

Figure 2.0 : Chance and assignable cause . Montgomery (2001)

In order to maintain and achieve quality improvement, minimizing process variation in manufacturing environment has become a major issue in quality control. Statistical quality engineering (SQE) tools have been developed for systematically reducing variability in the key process variables or quality characteristics of the product (Montgomery, 2001). Statistical process control (SPC) charting is one of the SQE tools that useful for monitoring and diagnosing process variation.

2.2 Statistical Process Control (SPC)

In general, the use of statistical tools in monitoring process variation can be visualised by Figure 2.1 below :

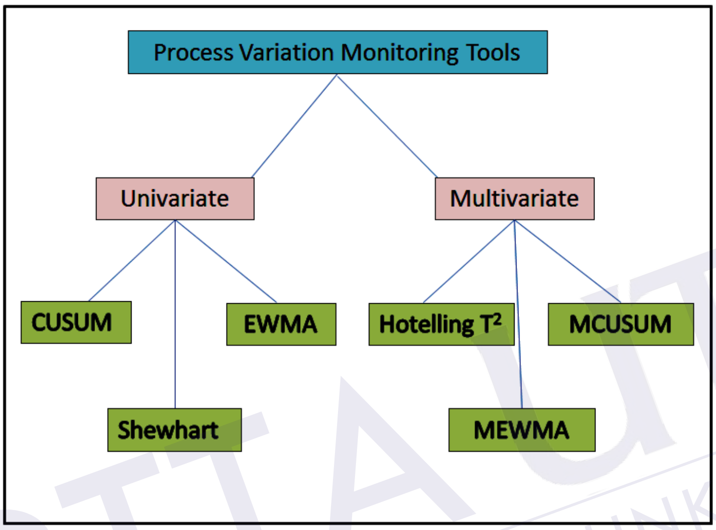

Figure 2.1 : Process variation monitoring tools

A primary tool used for SPC is the control chart. A control chart is a graphical representation of certain descriptive statistics for specific quantitative measurements of the process. In the following subsections, some widely used control charts will be reviewed. The aim of statistical process control (SPC) is to achieve higher quality of final product and lower the production loss due to defect product. Process monitoring with control chart is a basic tool of statistical process control. It monitors the behavior of a production process and signals the operator to take necessary action when abnormal event occurs. A stable production process is the key element of quality improvement. In this chapter, the traditional control chart – Shewhart control charts, which is a univariate statistical process control technique will be introduced.

2.3 Classical Statistical Control Schemes

The Shewhart $\bar{X}$ control chart, Cumulative Sum (CUSUM) control chart, and Exponentially Weighted Moving Average (EWMA) control chart are regarded as classical control schemes. Classical statistical control techniques focus on the monitoring of one quality variable at a time. In classical control schemes, an assumption is made that the values of the process mean and variance are known prior to the start of process monitoring.

A general model for the $\bar{X}$ control chart is given as follows. Let x be a sample statistic that measures some quality characteristic of interest, and suppose that the mean of x is μ_x and the standard deviation of x is δ_x. Then the control limits of the $\bar{X}$ control chart are $\mu_x \pm L\delta_x$ where L is defined as the "distance" of the control limits from the in-control mean, expressed in standard deviation units. If any point exceeds the control limits, the process will be deemed out-of-control. Investigation and corrective action are required to find and eliminate the assignable cause. A major disadvantage of the $\bar{X}$ control chart is that it can only use recent information, making it relatively insensitive to small to moderate shifts. Two control charts are proposed as excellent alternatives to the $\bar{X}$ control chart when small to moderate shifts are of primary interest. They are the CUSUM and EWMA control charts.

The CUSUM chart incorporates all information in the sequence of sample values by plotting the cumulative sums of the deviations of the sample values from a target value. There are two ways to represent cusums: the tabular cusum and the V-mask form of the cusum. Among these two cusums, as pointed out by Montgomery (2001), tabular cusum is preferable. The mechanics of the tabular cusum are as follows. Let x_i be the ith observation of the process. If the process is in control, then x_i follows a normal distribution with mean μ_0 and variance σ. Assume σ is known or can be estimated. Accumulate deviations from the target μ_0 above the target with one statistic, $C+$. Accumulate deviations from the target μ_0 below the target with another statistic, $C-$. $C+$ and $C-$ are one-sided upper and lower cusums, respectively.

The statistics are computed as follows:

$$C_i^+ = \max(0, x_i - (\mu_0 + k) + C_{i-1}^+) \tag{2.1}$$

$$C_i^- = \max(0, -x_i + (\mu_0 - k) + C_{i-1}^-) \tag{2.2}$$

where starting values are $C_0^+ = C_0^- = 0$ and k is the reference value. If either statistic (C_0^+ or C_0^-) exceeds a decision interval H, the process is considered to be out-of control.

The Exponentially Weighted Moving Average (EWMA) control chart is another control scheme useful for detecting small to moderate shifts. It is defined as

$$z_i = \lambda x_i + (1 - \lambda) z_{i-1} \tag{2.3}$$

where $0 < \lambda \leq 1$ is a constant and the starting value is the process target, i.e., $z_0 = \mu_0$. The control limits are :

$$\mu_0 \pm L\delta\sqrt{\frac{\lambda\ [1-(1-\lambda)^{2i}]}{(2-\lambda)}} \tag{2.4}$$

where L is the width of the control limits. If any observation exceeds control limits, an out-of-control condition happens.

2.4 Statistical Multivariate Process Control

In practice, many process monitoring and control scenarios involve several related variables, thus multivariate control schemes are required. The most common multivariate process-monitoring and control procedure is the Hotelling T^2 control chart for monitoring the mean vector of the process. The Hotelling T^2 chart was proposed by Hotelling H. (1947). There are two types of the Hotelling T^2 chart : one for sub-grouped data and the other for individual observations. Since the process with individual observations occurs frequently in the chemical and process industries, the Hotelling T^2 method for individual observations will be introduced in the following.

Suppose that *m* samples, each of size *n* = *1*, are available and that *p* is the number of quality characteristics observed in each sample. Let $\bar{x}$ and *S* be the sample mean vector and covariance matrix of these observations respectively. The Hotelling T^2 statistic is defined as :

$$T^2 = (x - \bar{x})' S^{-1} (x - \bar{x}) \qquad (2.5)$$

The Upper control limit (UCL) and Lower control limit (LCL) for monitoring processes are

$$UCL = \frac{p(m+1)(m-1)}{m^2 - mp} F_{\alpha,p,m-p} \qquad (2.6)$$

$$LCL = 0$$

where $F_{\alpha,p,m-p}$ – is the upper α percentage point of an *F* distribution with parameters *p* and *m* - *p*.

The Hotelling T^2 chart is a type of Shewhart control chart which only uses information from the current sample. Hence, it is relatively insensitive to small and moderate shifts in the mean vector. The MCUSUM control chart and MEWMA control chart, which are sensitive to small and moderate shifts, appear as alternatives to the Hotelling T^2 chart. Crosier (1988) proposed two multivariate CUSUM procedures. The one with the best ARL performance is based on the statistic:

$$C_i = \{(S_{i-1} + X_i)' \Sigma^{-1} (S_{i-1} + X_i)\}^{1/2} \qquad (2.7)$$

Where

$$S_i = \begin{cases} 0, & If\ C_i < k \\ (S_{i-1} + X_i)\left(1 - \frac{k}{C_i}\right), & If\ C_i > k \end{cases} \qquad (2.8)$$

With S0=0, and k>0. An out-of-control signal is generated when

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